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Machine learning

(main)

Supervised ML

- Regression
  - linear
  - Ridge & lasso
  - polynomial Reg.
  - Multi linear
  - Non-linear
  - OLS
  - Time series forecasting.
- classification
  - logistic
  - KNN
  - DT
  - Naive Byes
  - RF
  - XGB
  - GBM
  - SVM
  - ANN
  - catboost, adaboost

Unsupervised ML

- clustering
  - kmeans
  - DBscan
  - hierarchical
- apriori
- Recommdation
  - Content
  - Memory
    - User based
    - item based
- Dimentionality Reduction
  - PCA
  - tSNE
  - ICA
  - SVD
  - Auto Encoding.

Supervised ML →

We will start with Regression → linear

linear Regression

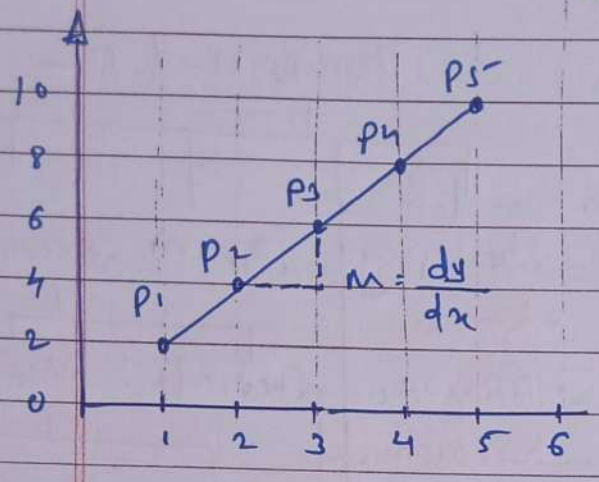
- Simple linear Regression (SLR)
- Multiple linear Regression (MLR)
- polynomial Regression

- Simple linear Regression (SLR) :- when for continuous output we have only one feature then it is called SLR

for Ex.

CGPA	package
6.0	2 LPA
7.2	3 LPA
8.9	6 LPA.

Basics of linier Regression



Equation of straigh line

$y = mx + c$

find value of m and c

$P_2 (2, 4) \longrightarrow x_1, y_1$

$P_3 (3, 6) \longrightarrow x_2, y_2$

$m = \text{slope} = \frac{y_2 - y_1}{x_2 - x_1} = \frac{6-4}{3-2}$

$m = \frac{2}{1} = 2$

slope means with every change in value of x how much differs in y

Intercept = c

$P_4 (x_3, y_3) \longrightarrow (4, 8)$

$y = mx + c$

$8 = 2(4) + c$

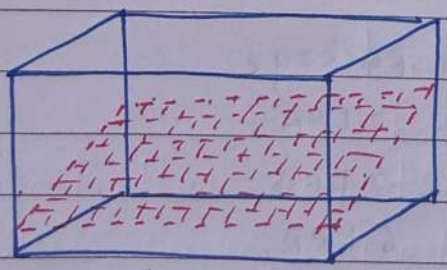
$8 - 8 = c = 0$

Inference : The above line eqn is function that relate x and y.

for given value of x we can find corresponding value of y.

what if we have two or more than two independent variable ?

⟶ then it is called multiple linear regression



(3D)

simple linear regression : $y = mx + c$

multiple linear regression

$y = a_1x_1 + a_2x_2 + a_3x_3 + \dots + a_nx_n + b$.

Advantages : 1) simple to implement

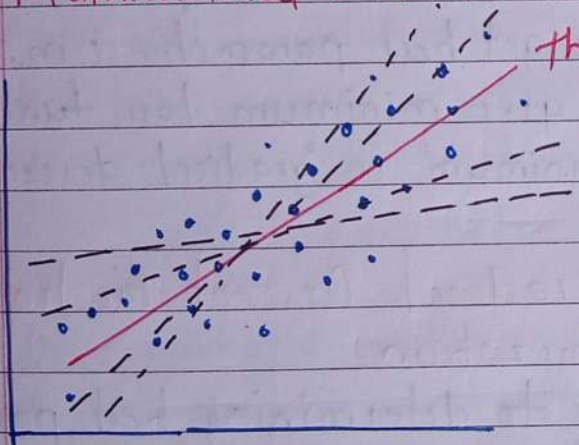
2) perform well on the data with linear relationship.

Disadvantages : 1) Not suitable for data having non-linear relationship.

2) underfitting issue

3) sensitive to outlier

Mathematical Understanding :-



this is called best fit line

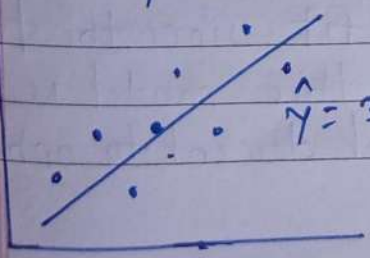
so here purpose is to find best fitted line (model) for linear regression.

{ this where loss function comes in picture }

- loss function measures how far an estimated value from its true value.
- it is helpful to determine which model performs better and which parameters are better.

$$\text{loss} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (m, c)$$

let try to understand with the Ex. $m = 3$, $c = 2$



x	y	$\hat{y}$
2	10	8
3	14	11
4	18	14
5	22	17
6	26	20.

Now find its loss function.

$$\text{loss} = \frac{[(10-8)^2+(14-11)^2+(18-14)^2+(22-17)^2+(26-20)^2]}{5}$$

$$= \frac{4+9+16+25+36}{5} = \frac{90}{5} = 18$$

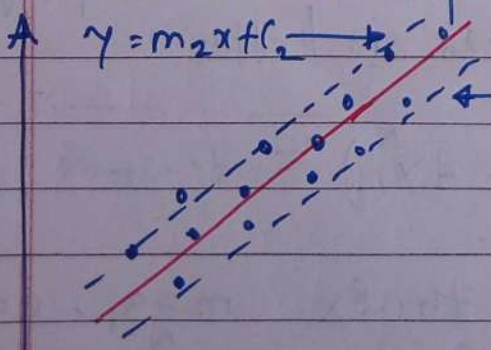
{ reason to take square :. so that positive and negative value may not cancel each other }

low loss value ⟶ High Accuracy
high loss value ⟶ low Accuracy

We can improve the model by some optimization technique called as "gradient descent" where repeate the process iteratively unbill we get best parameter (m, c) for which model will give minimum loss function. Called as 'global minimum" in 'gradient descent"

How we can use gradient Descent for linear regression for optimization.

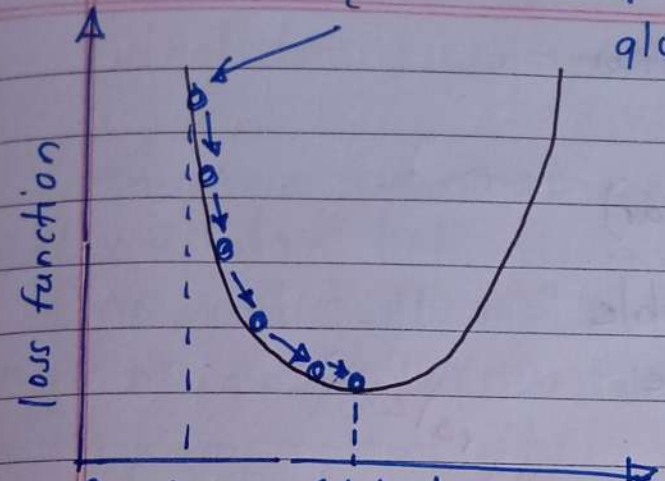
→ optimization refers to determining best parameter for model such that loss function of the model decreases as result of which model can predict more accurately.



{ m and c are the parameters }

here we can find model 3 is best fit since the loss function is least and thus this model is optimum this where we used gradient descent to optimize model.

{this will step down until reach down to global minimum by iterative process}



updated → $m = m_1 - L\,Dm$, $c = c_1 - L\,Dc$ (initial)

In machine learning: $w = w - L\,dw$, $b = b - L\,db$

m - slope
c - Intercept
w = weight
b = bias.

L - learning rate : it is magnitude of change that you want in parameter during iteration.

Dm : partial derivative of loss function w.r.t m
Dc : partial derivative of loss function w.r.t c.

$$Dm = \frac{\partial(\text{loss function})}{\partial m} = \frac{\partial}{\partial m}\left(\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2\right)$$

$$= \frac{-2}{n}\sum_{i=0}^{n} x_i(y_i - \hat{y_i})$$

Ily $Dc = \frac{\partial(\text{loss function})}{\partial c} = \frac{\partial}{\partial c}\left(\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2\right)$

$$= \frac{-2}{n}\sum_{i=0}^{n}(y_i - \hat{y_i})$$

In terms weigh and bias

$$y = wx + b$$

(weight) (biar)

x - independent Variable

Y - dependent Variable

w - weight

b - bias

updated — initial learning rate(α)

$$w = w - \alpha dw$$ ← change in Loss function w.r.t w

$$b = b - \alpha db$$ ← change in loss function w.r.t. b.

Learning rate:- it is tuning porometer in an ophimized on olgorithm that determine step size at each iteration while moving toword minimum of loss function.

$$dw = \frac{-2}{n} \sum_{i=0}^{\hat{}} x_i (y_i - \hat{y_i})$$

$$db = \frac{-2}{n} \sum_{i=0}^{\hat{}} (y_i - \hat{y_i}).$$

for Multiple linear Regression: for one target we have two or more than two independent varicbles.

prediction Equation for MLR

$$\hat{y} = a_1 x_1 + a_2 x_2 + \cdots a_n x_n + b.$$

and,

Regression Equation

$$y = \underbrace{a_1 x_1 + a_2 x_2 + a_3 x_3 + \cdots + a_n x_n + b}_{\text{predicted value}} + \varepsilon$$

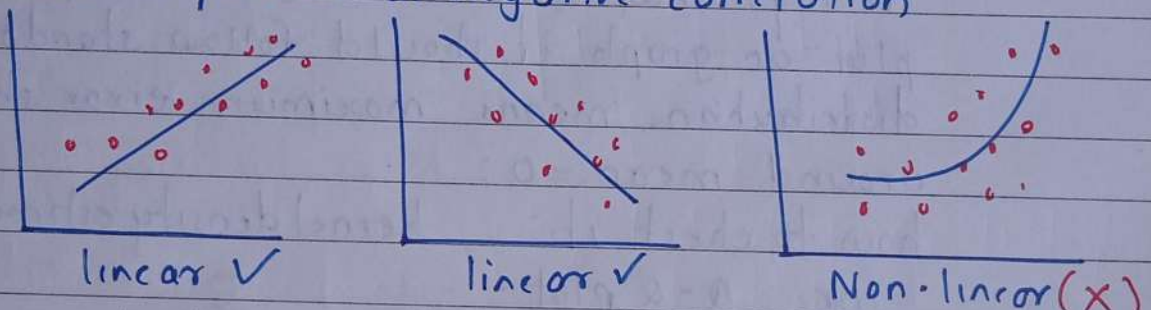
y: Actual Value. ε: Error

What are assumptions of linear Regression?

there are five main assumption in linear regression.

1. linear Relation between input and output.
2. No multicolinearity.
3. Normality of Residual.
4. Homoscedasticity.
5. No autocorrelation of error

1. **Assumption 1**: - there should be linear relation between individual feature and target (output) it could be positive or negative correlation



applicable to multiple linear problem as well. Not ok.
how to check this : scatter plot : (feature 1 Vs target) (feature 2 Vs target).

2. **Assumption 2**: - Multicollinearity .: it mean there all the feature should be independent or should not have any correlation among themselves.
why, what the problem?
In multi linear Regression model for 3D we draw a hyperplane.

$\hat{y} = a_1x_1 + a_2x_2 + a_3x_3 + b.$

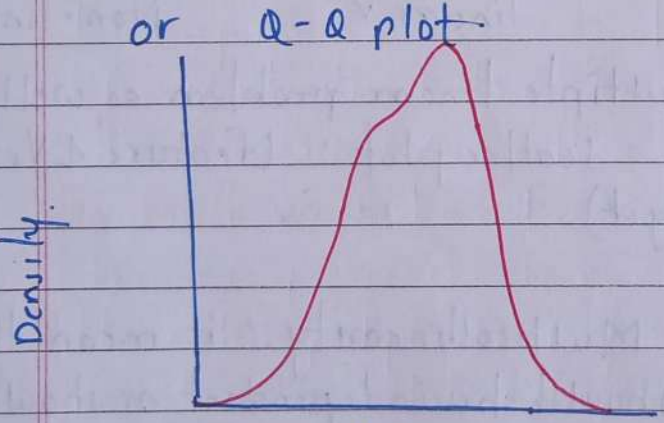
where a_1 represent what will be the change in y with respect to x_1 assuming x_2 and x_3 constant. but if it violate this assumption then model will not perform good. (Ex of two physics scientist)

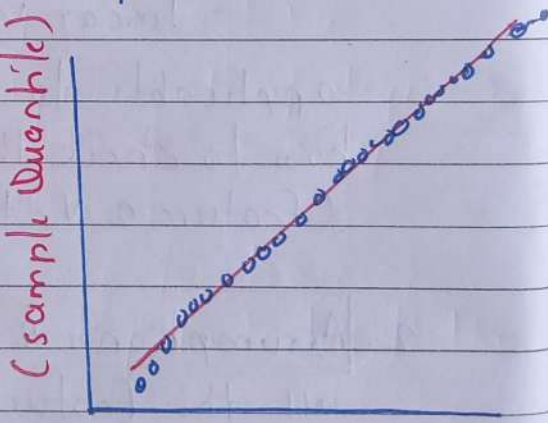
how to check multicollinearity :-

1) VIF (Variance Inflation factor) :-
if it is around 1 then feature don't have the issue and if it is 5 or more than that then that particular feature have multicollinearity issue and need to remove it

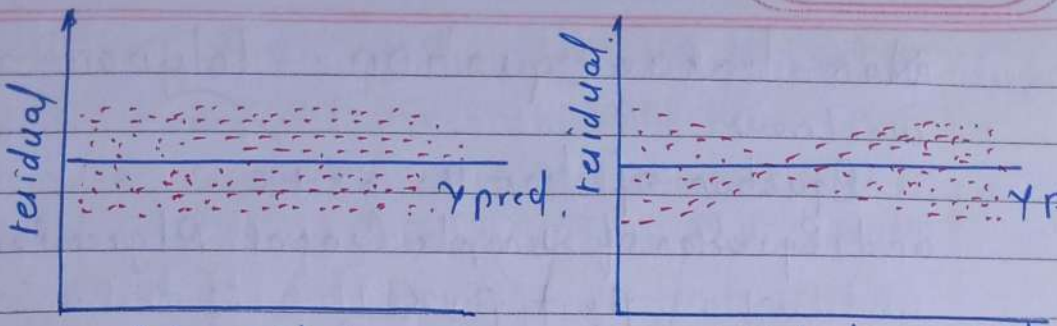
2) another method is to find out correlation between all the features (Heatmap)

3. **Assumption 3** - Normality of Residual.
it says that when error (actual - predicted) plot or graph it should follow standard normal distribution. means maximum error should around mean = 0.
how to check it: kernel density estimation (kde) or Q-Q plot





4. **Assumption 4**: Homoscedasticity.
some scattered / spread.
∴ spread of residual should be equally or uniformly scattered. if it is not it called as heteroscedasticity which is not desirable.

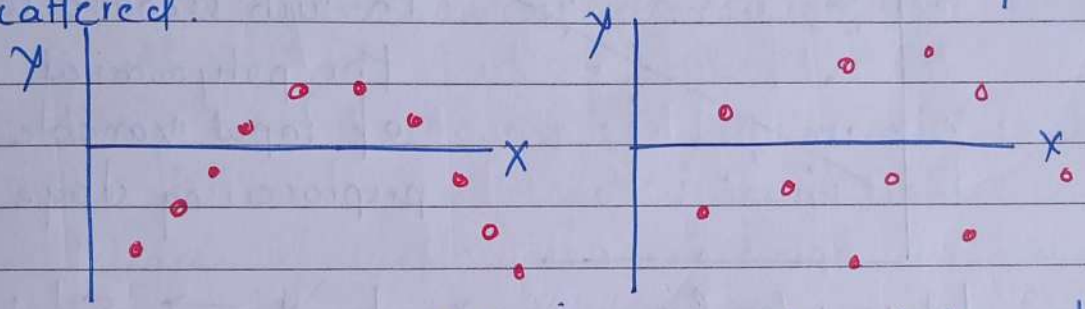


(desirable) (Not desirable)

how to check:- scatter plot (ypred, residual).

Assumption 5: No autocorrelation of Error.

if we plot the error there should not be any specific pattern instead it should randomly scattered.



positive Autocorrelation (Not desirable) Negative Autocorrelation (desirable).

how to check: pll. plot (residual)

Summary chart

Assumption	Severity	prediction	Inference
1) linear Relation	High	✓	✓
2) Multicollinearity	Medium	x	✓
3) Normality	low	x	✓
4) Homoscedasticity	High	✓	✓
5) Autocorrelation of Error	-	-	-

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Non-linear Equation - Polynomial Regression

we know

Equation of line $y = mx + c$

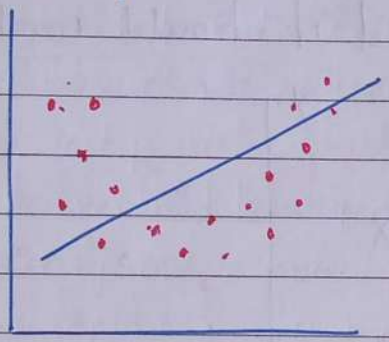
and Equation of simple Linear Regression

$$y = \beta_0 + \beta_1 x$$

and for multiple linear Equation.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_n x_n$$

this is applicable only when data is linear but what if data is not linear ?



In such scenario we extract the polynomial feature of input variable in preprocessing stage

let say for Ex x | y → 5 | 10

- for x we want to make polynomial of degree 2 then we will convert $x \rightarrow x^0, x^1, x^2, y$ so it will be 1, 5, 25
- this way we create a new data for training the extra polynomial feature try to extract thir non-linear relationship.
- its formula become for simple polynomial regression.

$$y = \beta_0 + \beta_1 x + \beta_2 x^2$$

For degree 3

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3.$$

★ Now how we will know the perfect value for the degree — since this is hyperparameter.

if we keep it low then may be it cause underfitting means it may be not able to learn the all attributes. and if we select very high then there is chance of overfitting or overlearned that's why our job is to find out optimum value

- In case if we have two features X_1, X_2, Y then for degree 2 our simple polynomial Equation would become

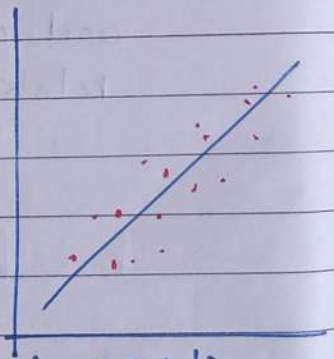
$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \beta_3 x_2 + \beta_4 x_2^4$$

Interview Que: why polynomial Eq^ essentially called as Linear Regression

Ans: when we talk about linear Regression we talk about relation between y and coefficient of features and degree of coefficient is still one and thus relation between y and coefficient is still linear

Ordinary least square :- (OLS Algorithm)

- it is method for estimating the parameters of linear regression model.
- it aim to find the values of the linear regression models parameters (i.e coefficient) that minimize the sum of squared residual.
- the residuals are differences between observed values of dependent variable and predicted values of dependent variable given w.r.t independent variable
- OLS Algorithom assumes that the errors are normally distributed with zero mean and constant variance and that there is no multicollinearity (high correlation) among the independent variables.
- other method like generalized least square or weighted least square, should be used in case when these assumption are not meet.



let understand with problem

X	1	2	3	4	5	6	7
y	1.5	3.8	6.7	9.0	11.2	13.6	16.

we will calculate the equation for the best fit line where all the point will be as close as possible by least square Method.

X	y	xy	x^2
1	1.5	1.5	1
2	3.8	7.6	4
3	6.7	20.1	9
4	9.0	36	16
5	11.2	56	25
6	13.6	81.6	36
7	16	112	49.
Σ 28	61.8	314.8	140.

$\Sigma x = 28 \quad \Sigma y = 61.8$

$\Sigma xy = 314.8 \quad \Sigma x^2 = 140$

$n = 7$

(number of data points)

$y = mx + b$

$$m = \frac{n\Sigma xy - \Sigma x \Sigma y}{n\Sigma x^2 - (\Sigma x)^2} = \frac{7(314.8) - (28)(61.8)}{7(140) - (28)^2}$$

$$m = \frac{473.2}{196} = 2.4142857.$$

$$b = \frac{\Sigma y - m\Sigma x}{n} = \frac{61.8 - 2.4142857(28)}{7}$$

$$b = -0.828571.$$

to get linear equation we should plug value in

$$y = mx + b.$$

~~$y = 2.41x$~~ $\quad y = 2.41x - 0.83.$

let test it for 2	$\hat{y}$	Yact
$y = 2.41(2) - 0.83 =$	3.99	3.8
$y = 2.41(5) - 0.83 =$	11.22	11.2
$y = 2.41(7) - 0.83 =$	16.04	16.

Syntax: statsmodel.api.OLS(y, x)

y: dependent variable x - independent variable.

- Import statsmodel.api as sm
  import pandas as pd.

- #reading data from csv
  df = pd.read_csv('train.csv')

- # defining the variables
  x = df['x'].tolist()
  y = df['Y'].tolist()

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```
# adding the constant term x
x = sm.add_constant(x)

# performming regression and fitting model.
result = sm.OLS(y, x).fit()

# print summary table
print(result.summary())
```

What is Ridge Regression (L2 Regularization)

Ridge regression is model tuning method that is used to analyse any data that suffers from multicollinearity this method performs L2 regularization when issue of multicollinearity occurs, least square are unbiased and variance are large this result in predicted values being far away from actual values.

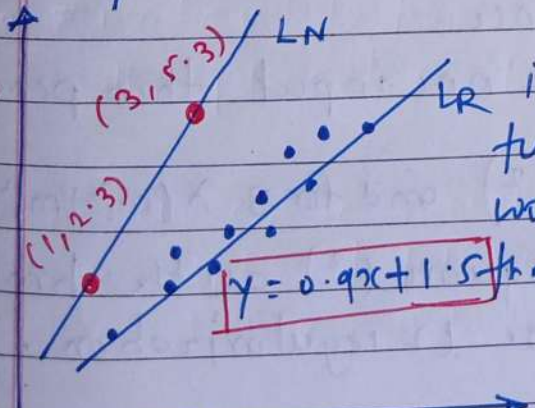
Regularization:- it is technique used to calibrate Machine learning model to minimize adjusted loss function and avoid overfitting and underfitting.

there are three types of regularization techniques:
1) Ridge Regression (L2 regularization)
2) Lasso Regression (L1 regularization)
3) Elastic Net (combo of Ridge and Lasso)

Ridge Regression:-
overfitting:- means your train acc is too high but test accuracy is very low.

$y = mx + b$

m or slope which is coefficient of x is define change in y, so to reduce overfitting means to reduce slope.



if we train the model only on two datapoint then best fit line would be the line which pass through both point

$y = 1.5x + 0.8$

Now we have to convey our model to choose LR and Not LN

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$$L = \underbrace{\sum_{i=1} (y_i - \hat{y}_i)^2}_{\text{before we were only reducing this term which is nothing but Error / Residual}} + \underbrace{\lambda(m^2)}_{\text{Now we add penalty which will add help for the first term}} \quad \text{---------- (1)}$$

λ = hyperparameter
m = slope.

Now we will calculate loss for both line for $\lambda = 1$ with eqn (1)

Since line is passing through both point perfectly that's why 1st term will be zero

$L = 0 + 1(1.5)^2$

$= 2.25$

$(2.3 - 0.9 - 1.5)^2 +$
$(5.3 - 2.7 - 1.5)^2 + (0.9)^2$

$= (0.1)^2 + (1.1)^2 + (0.9)^2$

$= 2.03$

here we getting significant reduction in loss for the new line
As our model can see this change it will select 2nd model although it will give bad accuracy on training since variance is significantly reduced although bias increased.

Why we called L^2 since
- if we have more than one input then penalty would be
$\lambda(m_1^2 + m_2^2)$ and for 3 $\lambda(m_1^2 + m_2^2 + m_3^2)$

Since we are doing square (^{2}) all the time we called it L2 Norm or L2 regularization.

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Lasso Regression (L1 Regularization)

- this is also help to reduce overfitting.
- In Ridge regression we have seen.

$$L = \underbrace{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}_{MSE} + \underbrace{\lambda \|w\|^2}_{\text{penalty term}}$$

$(w_1^2 + w_2^2 + \cdots w_n^2)$ — coefficient in MLR

Lasso is just another variation of Ridge

$$L = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \lambda \|w\|$$

OR

$$= MSE + \lambda [|w_1| + |w_2| + |w_3| + \cdots + |w_n|]$$

- In ridge regression for any value of λ there were always some value for coefficient of input feature but in lasso if you continously increase value of λ at certain point you will zero value for some of coefficient which are not important so here we unknowing doing feature selection and it is advantage of Lasso.
- so when you are working on high dimensional data and some feature are not imp we should prefer Lasso over Ridge.

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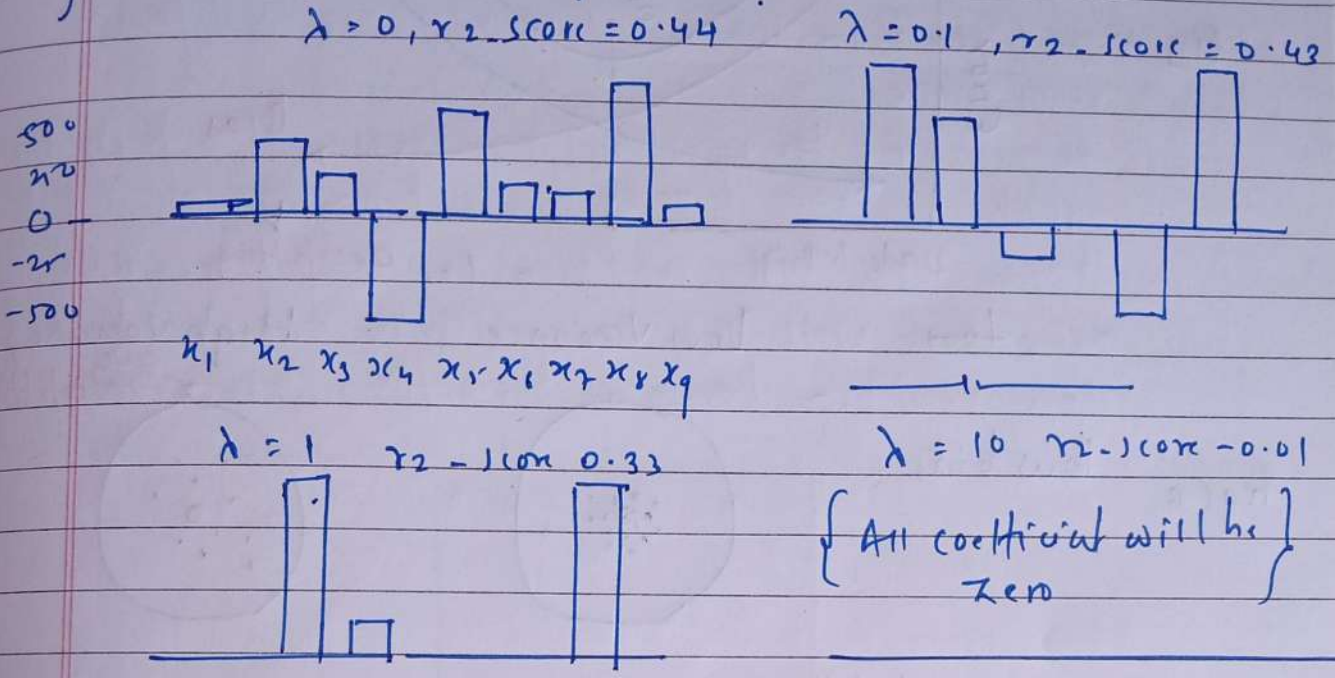
there are some keypoints need to discuss about Lasso.

1) How coefficient are affected. ?



2. Higher coefficient are affected more

- generally or you increased λ coefficient value will be decrease gradually toward zero penalize
- usually higher coefficients are affected first/rapidly
- for it we should be cautious for selecting optimum value to do proper feature selection

3. Impact on Bias and Variance

- As we know if λ increases, overfitting decreases (↓) which lead to increase in bias (↑)

High Bias → Underfitting

High Variance → overfitting

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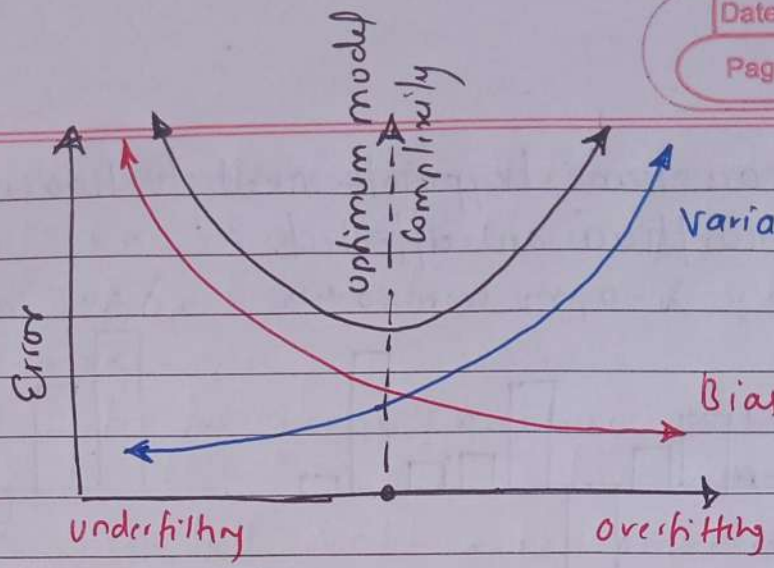
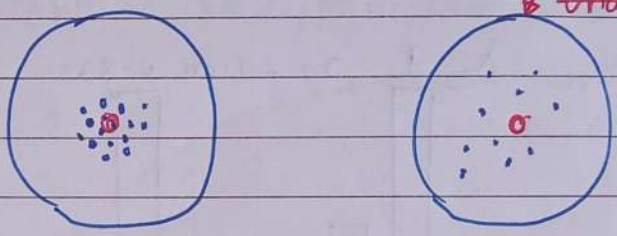
fig a.



low
Low Variance
High Variance
over ~~underfitting~~

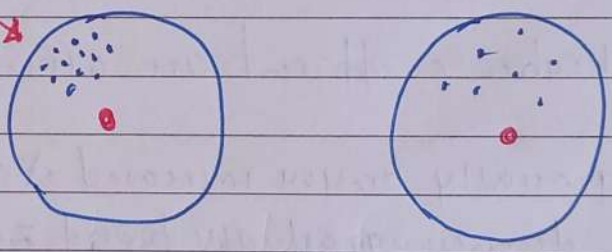
fig (b

low bias



underfitting

High bias



Bias-Variance Tradeoff.

- it is important to understand prediction errors (bias and variance) when it comes to accuracy in any ML Algorithm
- There is tradeoff between model's ability to minimize bias and variance which is referred to as best solution for selecting a value of regularization constant
- proper understanding of these error would help to avoid the overfitting and underfitting of a dataset while training algorithm.

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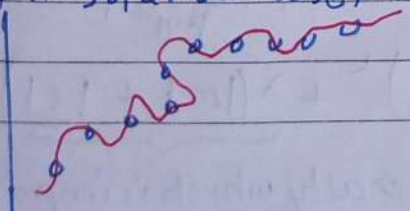
Bias :- Bias is known as difference between prediction values by ML model and correct values. Being high in biasing will give large error in training as well as testing. & thats why it is always recommended that algorithm should always be low biased to avoid underfitting.

- by high bias data is predicted is in straigh line format thus not fitting accurately in the data in the dataset such fitting called as underfitting.
- this happen the hypothesis is too simple or linear in nature

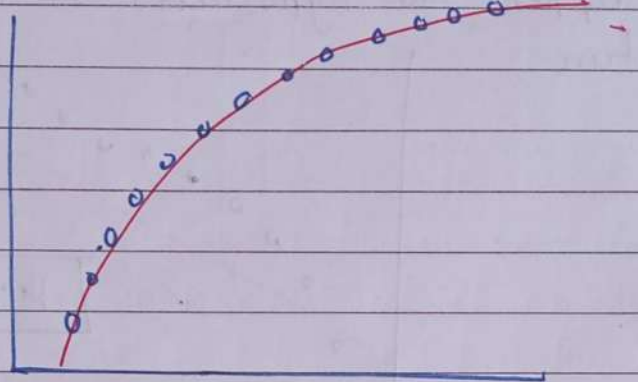
Variance . The variability of model prediction for given data point which tells us spread of our data is called variance of model.

- the model with high variance has a very complex fit to training data and thus not able to fit on the test data or data hasn't seen as result such model works very well on training data but has high error rates on test data
- when model is high on variance it is said to as overfitting of data. Overfitting is fitting the training set accurately via complex curve and high order hypothesis but is not the solution as the error with unseen data is high



high variance data look like follows

- Bias-Variance tradeoff :- if the algorithm is too simple (hypothesis with linear eq^n) then it may be on high bias and low variance and thus it is error prone.
- if error fit too complex (hypothesis with high degree equation) then it may be on high variance and low bias, in the latter condition the new entries will not perform well. there is something between both of these condition known as tradeoff or bias-variance tradeoff



4) Effect of Regularization on loss function

loss function :-

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

- it measures how far an estimated value from its true value
- if we are training on different models LR, DT, RF to know which model perform better and which parameters are better loss function is useful.

Elastic Net :- (L1+L2) : it is combination of both regularization technique

$$L_1 \text{ Reg} = \frac{\sum (y_i - \hat{y}_i)^2}{n} + \underbrace{\lambda(|m| + |c|)}_{\text{penalty which is imposed on parameter}}$$

hyperparameter

L2 reg : $\frac{\sum (y_i - \hat{y_i})^2}{n} + \underbrace{\lambda(m^2 + c^2)}_{\text{penalty}}$

Elastic (L1+L2) :-

$$\frac{\sum (y_i - \hat{y_i})^2}{n} + \lambda[(|m| + |c|) + (m^2 + c^2)]$$

adding combination percentage of Lasso & Ridge

$$\frac{\sum (y_i - \hat{y_i})^2}{n} + \lambda\left[\underbrace{c(|m| + |c|)}_{\text{lasso}} + \underbrace{(1-c)(m^2 + c^2)}_{\text{Ridge}}\right]$$

c is between 0 to 1

c = 1 Lasso

C = 0 RIDGE

c = 0.05 : 50% Ridge & 50% Lasso.

Summary :- Ridge is majority is going to focus on regularization but Lasso is going to focus on feature selection as well

- if my job is only feature selection i will go for Lasso and if i want regularization then i will go for Ridge. and if i want both then i would go for Elastic Net.

Time Series forecasting.

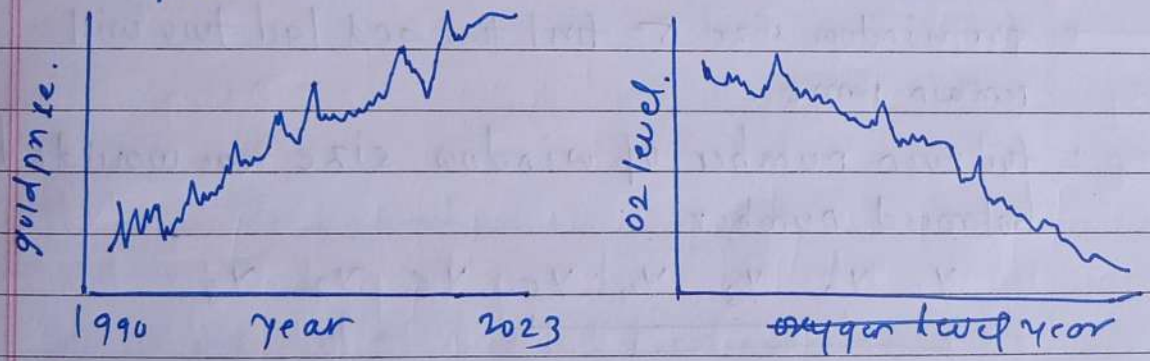
Time Series :- it is data which is index by time.

- the most important part of time series is sequence.

what we do with time series :- we capture the past data & based on that we predict for future this entire procedure is called forecasting

A) plotting time series
B) Component of time series
C) forecasting in time series
   - C1) Data based prediction
   - C2) model based prediction

A) line plot :-



- line plot gives holistic view or overall view.
- line plot gives basing understanding about long term i.e for long term what happened to my data.

- often time line plot are difficult to understand.

to overcome this we have technique called smoothing.

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how to do smoothing :-

moving average :- Ex i have rainfall data

Months	M_1	M_2	M_3	.....	M_{120}
data	y_1	y_2	y_3	.....	y_{120}

where M_1 - January
M_2 - february
M_3 - March.

for window size 3

$$y_2 = \frac{y_1 + y_2 + y_3}{3} \qquad y_3 = \frac{y_2 + y_3 + y_4}{3}$$ and so on —

- but it would not be same for first and last data point since they will not have one data point so their value will remain as it is.
- for window size 5 first two and last two will remain same.
- for even number of window size we wouldn't get balanced number

y_1 y_2 y_3 y_4 y_5 y_6 y_7 y_8

$$y_3 = \frac{y_2 + y_3 + y_4 + y_5}{4}$$ {giving high priority to future data}

$$y_3 = \frac{y_1 + y_2 + y_3 + y_4}{4}$$ {giving high priority to past data}

Solution is :-

$$= \frac{1}{2}\left[\frac{y_1 + y_2 + y_3 + y_4}{4}\right] + \frac{1}{2}\left[\frac{y_2 + y_3 + y_4 + y_5}{4}\right]$$

- How to figure out best window size?

1. Way of domain knowledge.
Eg. sales of AC is based on season like in summer it sold out rapidly whereas in winter is not seem that like expected.
so here we can assume or try window size 3/4

2. when we don't have domain knowledge another way is by calculating size for all and check where we it becomes smooth.

Components of time series:
it generally has three components:
1) Trend — holistic view - Moving average
2) Seasonality - periodic change
3) Resid — Noise or Error - lesser the better.

Decomposition of T.S [Trend, Seasonality, Noise]
- Trend:- find optimum window size

- To find seasonality & Noise substract trend from original data.

Let say we have data 2001 to 2010

Month M_1 M_2 M_3 M_4 ..... M_{120}

data Y_1 Y_2 Y_3 Y_4 ..... Y_{120}

Trend : $T_1 = M_1$, $T_2 = \frac{M_1+M_2+M_3}{3}$, $T_3 = \frac{M_2+M_3+M_4}{3}$

Seasonality : $S_1 = Jan = \frac{T_1+T_{13}+T_{25}+\cdots T_{109}}{10}$

$S_2 = Feb = \frac{T_2+T_{14}+T_{26}+\cdots T_{110}}{10}$

Noise : $N_1 = Y_1 - T_1 - S_1$, $N_2 = Y_2 - T_2 - S_2$, ... $N_{120} = Y_{120} - T_{120} - S_{120}$.

forecasting in time series.

Data based forecasting :-

① Simple Exponential :- it is applicable to those time series where there is no trend no seasonality.

② Double Exponential :- it is only performed good for those time series where it only have trend but not seasonality.

③ Holt winter's model - (Triple Exponential) it is performed well where there is both trend as well as seasonality (when you don't know whether time series have trend or seasonality then Holt winter is best)

→ Simple Exponential :-

Day	D_1	D_2	D_3	...	D_{199}	D_{200}	D_{201}
Temp	t_1	t_2	t_3		t_{199} ←	t_{200}	
						Today →	(predict)

what will be the easiest way to predict for tommorow's temp when we have data upto today?

① taking Avg :- $\frac{t_1 + t_2 + t_3 + \cdots + t_{200}}{200} = x$.

but this not good method since temp varies a lot throughout year summer to winter

② another way is whatever is today's temp it will same for tomorrow.

$t_{day\,200} = 25.7°$

$t_{day\,201} = 25.7°$.

Simple Exponential :- instead of taking all 200 data into consideration. we will take recent data for prediction.

- Simple Exponential try to calculate the component in local Average.

Day	D_1	D_2	D_3	D_4	. . .	D_{199}	D_{200}
temp	t_1	t_2	t_3	t_4		t_{199}	t_{200}
	L_1	L_2	L_3	L_4		L_{199}	L_{200}

- local Average at Day 4 i.e L_4 will be combination of two component yesterday's Local Average and today temp

L_4 / \ t_4 $\quad = L_4 = \frac{1}{2} L_3 + \frac{1}{2} t_4$

L_3

Note $L_1 \rightarrow t_1$ Since there is no previous record. Simple Exponential is applicable second point onwards.

Mathematical Understanding :-

$$L_{200} = \frac{1}{2} L_{199} + \frac{1}{2} t_{200} \quad \text{—— (1)}$$

$$L_{199} = \frac{1}{2} L_{198} + \frac{1}{2} t_{199} \quad \text{—— (2)}$$

$$L_{200} = \frac{1}{2}\left[\frac{1}{2} L_{198} + \frac{1}{2} t_{199}\right] + \frac{1}{2} t_{200} \quad \text{.. 2 in (1)}$$

$$= \frac{1}{4} L_{198} + \frac{1}{4} t_{199} + \frac{1}{2} t_{200} \quad \text{—— (3)}$$

$$L_{198} = \frac{1}{2} L_{197} + \frac{1}{2} t_{198} \quad \text{—— (4)}$$

put (4) in (3)

$$\frac{1}{4}\left[\frac{1}{2} L_{197} + \frac{1}{2} t_{198}\right] + \frac{1}{4} t_{199} + \frac{1}{2} t_{200}$$

$$\frac{1}{8} L_{197} + \frac{1}{8} t_{198} + \frac{1}{4} t_{199} + \frac{1}{2} t_{200}$$

if i rearrange this, we will get

$$L_{200} = \frac{1}{2} t_{200} + \frac{1}{4} t_{199} + \frac{1}{8} t_{198} + \frac{1}{16} t_{197} \ldots$$

$\left(\frac{1}{2}\right)^1 \quad \left(\frac{1}{2}\right)^2 \quad \left(\frac{1}{2}\right)^3 \quad \left(\frac{1}{2}\right)^4$

- from current datapoint weightage of coefficient reduce exponentially. whereas in simple average every coefficient were getting equal average.

let understand with short Example.

Day	1	2	3	4	5	6
Score	1	2	1	2	1	3

$L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_5 \rightarrow L_6$

$L_1 = 1$, $L_2 = \frac{L_1 + S_2}{2} = \frac{1+2}{2} = 1.5$

$L_3 = \frac{L_2 + S_3}{2} = \frac{1.5+1}{2} = \frac{2.5}{2} = 1.25$

$L_4 = \frac{L_3 + S_4}{2} = \frac{1.25+2}{2} = \frac{3.25}{2} = 1.625$

$L_5 = 1.3125$, $L_6 = 2.1562$

All future prediction going to be last available local Average.

Double Exponial :- it contain trend but no seasonality.

- we can't always rely on local Average because for ex. if chocklate price increase by Rs 1 each day.

Day	1	2	3	4	5	6
price	1	2	3	4	5	9

L_6

L_6 = around 4.2 which is not true.

Hence we need consider a trend as well., that's why we need both trend as well as local Average.

for local Avg

L_{200}

L_{199} (yesterday local Avg) Y_{200} (today's data)

∴ but local avg is also expected to change by some amount.

there is little modification in local Average

$$L_{200} = \frac{1}{2} L_{199} + \frac{1}{2} Y_{200}$$

$$L_{200} = \frac{1}{2}(L_{199} + T_{199}) + \frac{1}{2} Y_{200}$$

↑ trend is added.

$$T_{200} = \frac{1}{2} T_{199} + \frac{1}{2}(L_{200} - L_{199})$$

↑ (today's trend)

change in local Average from yesterday to today

Raw data	Y_1	Y_2	Y_3	Y_4	. . . .	Y_{200}
Local Avg	L_1	L_2	L_3	L_4	. . . .	L_{200}
Trend	T_1	T_2	T_3	T_4	. . . .	T_{200}

so from raw data we will calculate Local Avg & trend.

$L_1 = 0$

$T_1 = 0$

$$L_2 = \frac{1}{2}(L_1 + T_1) + \frac{1}{2}(Y_2)$$

$$T_2 = \frac{1}{2}(T_1) + \frac{1}{2}(L_2 - L_1)$$

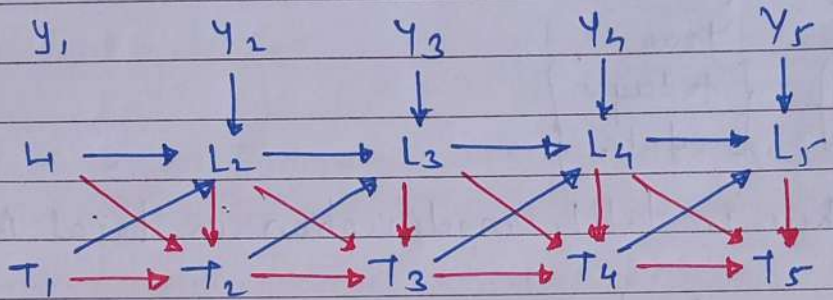
Let us understand with Example, we will solve problem, both Simple Exponential & Double Exponential.

Day	1	2	3	4	5
price (Y)	1	2	3	4	5
L(S)	1	1.5	2.25	3.125	4.0625
L(D)	1	1.5	2.375	3.4687	4.6484

$\frac{1+2}{2} = 1.5$

$\frac{1.5+3}{2} = \frac{4.5}{2} = 2.$

Now we will calculate with Double Exponential.



$L_2 = \frac{1}{2}(L_1 + T_1) + \frac{1}{2}(Y_2)$

$T_2 = \frac{1}{2}(T_1) + \frac{1}{2}(L_2 - L_1)$

$L_2 = \frac{1}{2}(1+0) + \frac{1}{2}(2) = \frac{1}{2} + 1 = 1.5$

$T_2 = \frac{1}{2}(0) + \frac{1}{2}(1.5-1) = 0 + \frac{0.5}{2} = 0.25$

$L_3 = \frac{1}{2}(L_2 + T_2) + \frac{1}{2}(Y_3)$

$= \frac{1}{2}(1.5+0.25) + \frac{1}{2}(3) = \frac{1}{2}(1.75) + 1.5$

$= 0.875 + 1.5$

$= 2.375$

$T_3 = \frac{1}{2}T_2 + \frac{1}{2}(L_3 - L_2)$

$= \frac{1}{2}(0.25) + \frac{1}{2}(2.375 - 1.5)$

$= 0.125 + 0.4375$

$= 0.5625$

$L_4 = \frac{1}{2}(L_3 + T_3) + \frac{1}{2}(Y_4)$

$= \frac{1}{2}(2.375 + 0.5625) + \frac{1}{2}(4)$

$= \frac{2.9375}{2} + 2$

$= 1.4687 + 2 = 3.4687$

$T_4 = \frac{1}{2}(T_3) + \frac{1}{2}(L_4 - L_3)$

$= \frac{1}{2}(0.5625) + \frac{1}{2}(3.4687 - 2.375)$

$= 0.28125 + 0.5(1.0937)$

$= 0.28125 + 0.54685$

$= 0.8281$

$L_5 = \frac{1}{2}(L_4 + T_4) + \frac{1}{2}(Y_5)$

$= \frac{1}{2}(3.4687 + 0.8281) + \frac{1}{2}(5)$

$= 2.1484 + 2.5$

$= 4.6484$

$T_5 = \frac{1}{2}T_4 + \frac{1}{2}(L_5 - L_4)$

$= \frac{1}{2}(0.8281) + \frac{1}{2}(4.6484 - 2.4687)$

$= 0.41405 + 0.5(1.1797)$

$= 0.41405 + 0.58985$

$= 1.0039$

T_1	T_2	T_3	T_4	T_5	} Trend is increased.
0	0.25	0.56	0.82	1.0039	

	Actual	Predicted.
Simple Exponential	4.0625	5
Double Exponential	4.6484	5

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Holt's winter model :- which contain both trend & seasonality.

Here along with local Average we will find out trend as well as seasonality.

time series data

	Y_1	Y_2	Y_3	Y_{200}
A	L_1	L_2	L_3	L_{200}
rend	T_1	T_2	T_3	T_{200}
sonality	S_1	S_2	S_3	S_{200}

for 200 Months ⟶ 16 yrs - 7 months
for seasonality — periodic time of 12 months

let first convert it into double exponential problem. by subtracting seasonality from time series

$Y_1 - S_1$, $Y_2 - S_2$, $Y_3 - S_3$ - - - $Y_{200} - S_{200}$

$$L_{200} = \frac{1}{2}(L_{199} + T_{199}) + \frac{1}{2}(Y_{200} - S_{200}) \quad \text{—— (1)}$$

{ Note Since $Y_{200} = Y_{200} - S_{200}$ }

$$T_{200} = \frac{1}{2}(T_{199}) + \frac{1}{2}(L_{200} - L_{199}) \quad \text{—— (2)}$$

$$S_{200} = \frac{1}{2}(S_{200} - 12) + \frac{1}{2}(S_{200})$$

↑

From (1) we can get to know to get L_{200} we substract S_{200} from Y_{200} then now S_{200} we can do $Y_{200} - L_{200}$.

$$S_{200} = \frac{1}{2}(S_{200} - 12) + \frac{1}{2}(Y_{200} - L_{200}) \quad \text{—— (3)}$$

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if you are carefully observe then you find there is loop between ③ equations.

for L_{200} we need S_{200} for S_{200} we need L_{200}

Since seasonality is periodic

$$S_{200} = S_{188}$$

in eq^ ① $S_{200} = S_{188}$

$$L_{200} = \frac{1}{2}(A_{99} + T_{199}) + \frac{1}{2}(Y_{200} - S_{188})$$

$$T_{200} = \frac{1}{2}(T_{199}) + \frac{1}{2}(L_{200} - L_{199})$$

$$S_{200} = \frac{1}{2}(S_{200-12}) + \frac{1}{2}(Y_{200} - L_{200})$$

Summary table.

Model	when we can apply	what should be future prediction	hyperparameter
Simple Exponential	No trend No seasonality.	last possible local Avg = all future prediction	1
Double Exponential	only trend No seasonality	last possible local Avg & changed trend	2
Tripple Exponential	both trend and seasonality.	local Average + trend + seasonality.	3.

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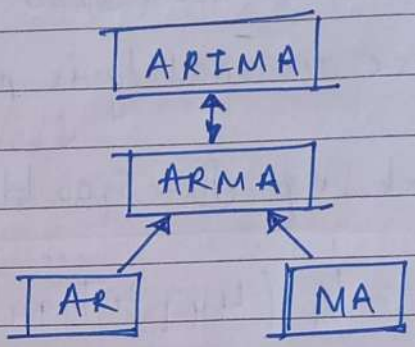
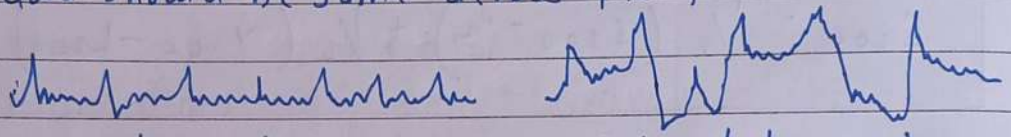
Model Based forecasting :-

Basically there are three models.

1) AR
2) MA
3) ARMA
4) ARIMA



Here data must be stationary. it means distribution of data should be same across the time



(stationary) ✓ (Not stationary).

if we have stationary data then go for model based otherwise databased since there is no any condition

AR (Auto Regressive) : AR is completely depend upon past data and nothing else for future prediction

MA: Moving Average : future data is only depend only external outsiders factors.

ARMA :- future data only going to deal with both past data data and external factors.

AR model :-

In regression $Y = \alpha x + \beta t + \varepsilon$

future y $Y_t = \alpha y_{t-1} + \beta + \varepsilon$

past y, Beta, Error

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Here future data is only depend on past data if it would depend on past two data

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \beta + \varepsilon \quad AR(2)$$

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \alpha_3 y_{t-3} + \beta + \varepsilon \quad \ldots AR(3)$$

How to select Best possible model. AR1, AR2, AR3 ~~AR1~~ ~~obs~~ based on test data accuracy whichever will perform good will finalize that.

MA : Moving Average Here my future data is only depend upon external factors.
Ex rate of some production which depends upon seasons. (grain or fruit) due to natural calamities.

data	Y_1	Y_2	Y_3	. . .	Y_t
External factors	ε_1	ε_2	ε_3	. . .	ε_t

$$y_t = \alpha \varepsilon_{t-1} + \beta + \varepsilon_t \quad \ldots MA(1)$$

this year data / last year data / constant

$$y_t = \alpha_1 \varepsilon_{t-1} + \alpha_2 \varepsilon_{t-2} + \beta + \varepsilon_t \quad \ldots MA(2)$$

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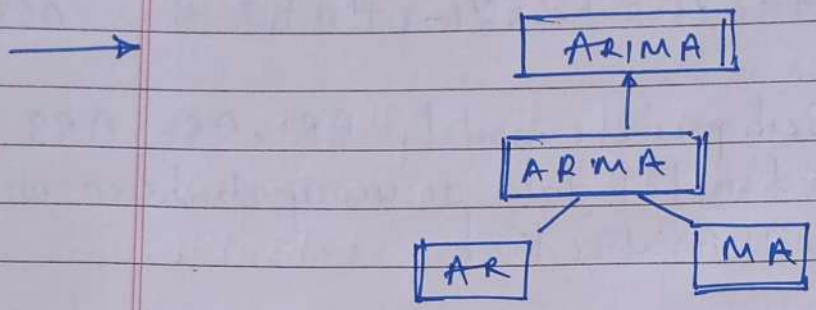
Model based forecasting.

1. AR
2. MA
3. ARMA (AR + MA)
4. ARIMA (which is comibhy ARMA itself)



AR → future prediction are completely depend on past data, it is just copy of regression model.

$y = \alpha x + \beta + \varepsilon$

target variable — y; prediction — $\alpha x + \beta$; error — ε

$y_t = \alpha y_{t-1} + \beta + \varepsilon$ ——— AR(1)

αy_{t-1}: past data

it if is depend on one past data

$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \alpha_3 y_{t-3} + \beta + \varepsilon$

y_t: tomorrow; y_{t-1}: today; y_{t-2}: yesterday; y_{t-3}: day before yesterday

it is similar to SLR

SLR:	$y = \alpha x + \beta + \varepsilon$	$AR(1) = \alpha y_{t-1} + \beta + \varepsilon_t$
2 features	$y = \alpha_1 x_1 + \alpha_2 x_2 + \beta + \varepsilon$	$AR(2) = \alpha y_{t-1} + \alpha y_{t-2} + \beta + \varepsilon_t$

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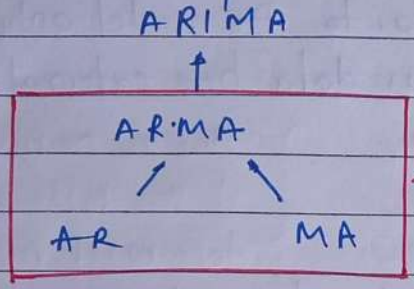
- one of the necessary condition for apply these data is data should be stationary i.e it means distribution of data should be same across all the data point.
- Since among all four model ARMA, AR and MA are very critical for that we must sure that data should be stationary.



← Since they are critical must sure for stationary data.

MA → Moving Average :- here future prediction are completely depend upon external factors.

production of nil →	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7
Error due to external factor →	ε_1	ε_2	ε_3	ε_4	ε_5	ε_6	ε_7

- when we say our data is only depending on last time point for example for 8th year

$$Y_8 = \alpha \varepsilon_7 + \beta + \varepsilon_8$$

so general formula is

$$Y_t = \alpha(\varepsilon_{t-1}) + \beta + \varepsilon_t$$ ——— Moving Avg (MA)

depend on External Error factors.

$$Y_t = \alpha(y_{t-1}) + \beta + \varepsilon_t$$ ——— Auto Regressive (AR)

depend on past data.

for MA(2) and MA(3) equation would be.

MA(2): $y_t = \alpha_1 \varepsilon_{t-1} + \alpha_2 \varepsilon_{t-2} + \beta + \varepsilon$

MA(3): $y_t = \alpha_1 \varepsilon_{t-1} + \alpha_2 \varepsilon_{t-2} + \alpha_2 \varepsilon_{t-3} + \beta + \varepsilon$.

- it is exactly similar to AR model only difference is instead of previous data here external factors are integrated.

ARMA: it is combination of AR and MA model.

ARMA(1,1)
AR(1) + MA(1)

ARMA(P, q) = AR(P) + MA(q)

$y_t = \alpha_1 y_{t-1} + \beta_1 \varepsilon_{t-1} + \beta_0 + \varepsilon_t$.

if $\beta_1 \varepsilon_{t-1} = 0$ then it will be AR(1)

$y_t = \alpha_1 t_{1-1} + \beta_1 \varepsilon_{t-1} + \beta_0 + \varepsilon_t$.

if $\alpha_1 t_{1-1} = 0$ then it will be MA(1)

- thats why you don't need to put MA and AR model seperately.
- if you think your model mostly inclined to MA then we can put AR component zero if model inclined to AR then we can put MA component zero.

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- thing we need to take of for these three models.

i) stationary :- if it is stationary we gonna directly used ARMA instead of using AR and MA model seperately.

ii) ARMA model has two hyperparameter (P, q)
P correspondes to AR and q corresponds to MA

how to choose best value of p and q.
by creating multiple model in range of (0 to 5) for each p and q

p : {0, 1, 2, 3, 4, 5} = 6 6 x 6 = 36
q : {0, 1, 2, 3, 4, 5} = 6

since 0,0 is not possible pair we have 36 - 1 = 35

ARIMA :- ARIMA doesn't care about data is stationary or Not.

this not a new model but extension of ARMA
ARIMA - Auto Regressive integrated moving average.

- if transformed data from original data follows ARMA model then original data will must follow ARIMA.

Y_1 Y_2 Y_3 Y_4 . . . . Y_n.
↓ ↓ transformed data ↓ ↓
Z_1 Z_2 Z_3 Z_4 Z_n

if this $\{Z_1, Z_2 \cdots Z_n\}$ follows ARMA then $(Y_1, Y_2 \cdots Y_n)$ will must follow ARIMA.

for ex.

Bank balance of Every month.

$y_1 \quad y_2 \quad y_3 \quad y_4 \quad \ldots \quad y_t \leftarrow$ (today)

{ here money is added every month not due to new added but due to interest }

what will interest added each month

$z_1 \quad z_2 \quad z_3 \quad z_4 \quad z_t$

where $z_1 = y_2 - y_1$
$z_2 = y_3 - y_2$
$z_3 = y_4 - y_3$

} this is newly constructed data if this follow ~~ARMA~~ then parent data will follow ARIMA

~~ARMA~~ has two component (P, q) whereas ARIMA has three component (P, q, d).

d → degree of substraction

d - for substraction of consecutive numbers.

d = 1	d = 2	d = 3
$z_1 = y_2 - y_1$	$z_1 = y_3 - y_1$	$z_1 = y_4 - y_1$
$z_2 = y_3 - y_2$	$z_2 = y_4 - y_2$	$z_2 = y_5 - y_2$
⋮	⋮	⋮
$z_{100} \quad y_{101} - y_{100}$	$z_{100} = y_{102} - y_{100}$	$z_{100} = y_{103} - y_{100}$

what is lifecycle of ARIMA

Transformation

Raw data → Substraction degree → Apply ~~ARMA~~ on New Model.

Summary table.

Model	No of paromiter	Conditions	depends on.
AR	1	stationary	past
MA	1	stationary	External factor
ARMA	2	stationary	past + External factor
ARIMA	3	No need - since I'm transforming the data.	

forecasting

Data Based

there is no previous condition

- Simple Expontial → No trend, No seasonality.
- Double Expontial → trend ✓ but No seasonality.
- Holt winters → both trend & seasonality.

{ whenever we don't know which to used we can used directly Holt winter }

Model Based

AR MA ARMA ARIMA

{ stationary data }

{ when we are not sure directly go for ARIMA }

Evaluation of time series Model.

there are two matrix we gonna used.

① Mean Square Error ② MAPE score.

Mean Square Error.

let say i have so many future data.

Actual	Prediction
Y_t	$\hat{Y}_t$
Y_{t+1}	$\hat{Y}_{t+1}$
Y_{t+2}	$\hat{Y}_{t+2}$

$$MSE = \frac{(Y_t - \hat{Y}_t)^2 + (Y_{t+1} - \hat{Y}_{t+1})^2 + (Y_{t+2} - \hat{Y}_{t+2})^2}{n}$$

② MAPE Score. (Mean Absolute Percentage Error)

let compare 2 scenarios.

	S1	S2
Actual	3	1000
predicted	2	999.

which is more accurate ?

{ if you try MSE for both it would be same }

it means sometime we are not interested in amount of error but percentage of error

· formula for MAPE scores is

$$\frac{|y_A - y_P|}{y_A}$$ — this is value of percentage

final ans $= \frac{|3-2|}{3} = \frac{1}{3} = 33.3\%$.

Second case : $\left|\frac{1000-999}{100}\right| = 0.001$

0.01%

Since we are not only concerned about Absolute error always but absolute percentage error also.

Exercies :- Calculate the MSE and MAPE score

Actual	Predicted
5	10
20	15
30	25

$$MSE = \frac{(5-10)^2 + (20-15)^2 + (30-25)^2}{3}$$

$$= \frac{(-5)^2 + (5)^2 + (5)^2}{3} = 25$$

MAPE score :

$$\left|\frac{y_A - y_P}{y_A}\right| = \left|\frac{5-10}{5}\right| = -5/5 = -1 = 100\%.$$

$$= \left|\frac{20-15}{20}\right| = 25\%.$$

$$= \left|\frac{30-25}{25}\right| = 16.6\%.$$

Mean abs error = $\frac{100+25+16.6}{3} = 47.2$

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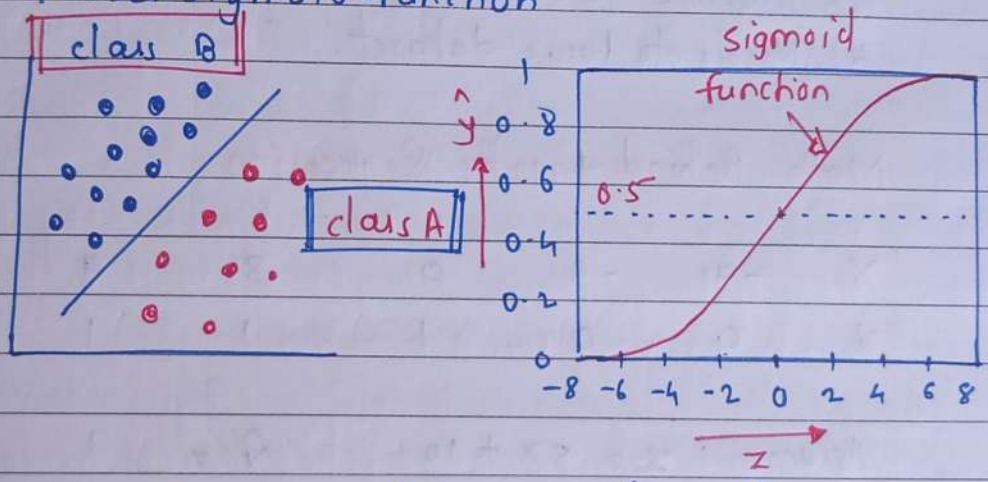
Classification Algorithm

1) Logistic Regression
2) SVM
3) KNN
4) Decision Tree
5) Random forest

.
.

1) Logistic Regression :-

1. it is supervised learning model.
2. it is classification model and best for binary classification.
3. it use sigmoid function



$$\text{Sigmoid function} = \hat{y} = \frac{1}{1 + e^{-z}}$$

where $z = wx + b$.

$(mx + c)$ - eq^ of line

slope m → weight w
intercept c → bias b

- $\hat{y}$ = probability that $(y=1)$

$\hat{y} = p(y=1|x)$ ... {probability of y being 1 for given value of x}

x = input features
w = weights (it will be in this format)
{number of weight equal to number of feature in the dataset}
b = bias
$\hat{y} = \sigma(z)$.

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Advantage: 1) Easy to implement
2) perform well on data with linear relationship
3) less prone to overfitting for low dimensional dataset.

Disadvantage :- 1) High dimensional dataset causes overfitting.
2) difficult to capture complex relationship in dataset
3) sensitive to outlier
4) Needs to large dataset.

Math Behind logistic Regression.

X	-9	-8	0	8	9
Y	0	0	1	1	1

Assume $\cdot z = 5x + 10$ $\quad \hat{y} = \frac{1}{1+e^{-z}}$

$x = -9$	$x = -8$	$x = 0$	$x = 8$	$x = 9$
$z = 5(-9)+10$ $= -35$	$z = 5(-8)+10$ $= -30$	$z = 5(0)+10$ $= 10$	$z = 5(8)+10$ $= 50$	$z = 5(9)+10$ $= 55$
$\hat{y} = \frac{1}{1+e^{35}}$	$\hat{y} = \frac{1}{1+e^{30}}$	$\hat{y} = \frac{1}{1+e^{10}}$	$\hat{y} = \frac{1}{1+e^{50}}$	$\hat{y} = \frac{1}{1+e^{55}}$
$\hat{y} = 0$	$\hat{y} = 0$	$\hat{y} = 1$	$\hat{y} = 1$	$\hat{y} = 1.$

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Inference :- if z value is large positive number.

$$\hat{y} = \frac{1}{1+0} \cong \hat{y} = 1.$$

if z is large negative number.

$$= \frac{1}{1 + (\text{large positive number})}$$

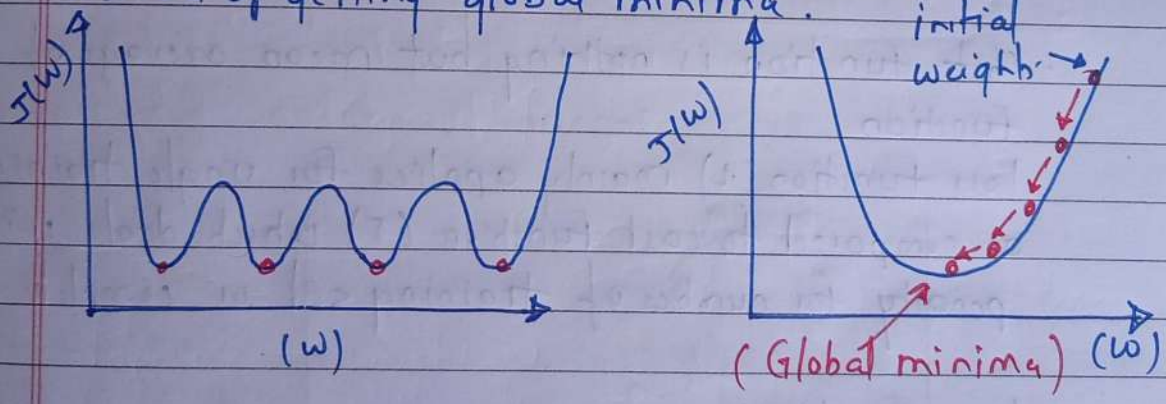
$$\hat{y} = 0.$$

loss function & cost function for Logistic Regression.

- loss function measures how far an estimated value is from true value.

$$\text{loss function for linear regression} = \frac{1}{n} \sum_{i=1}^{n} (y_i - y_{pred})^2$$

if we use this function we will get many local minima instead of getting global minima.



- Binary cross entropy loss function (or) log loss.

$$L(y, \hat{y}) = -(y \log \hat{y} + (1-y) \log(1-\hat{y}))$$

Here,

$y \longrightarrow 0$ or 1

& $\hat{y} \longrightarrow 0$ to 1 (probability could be continuous)

when $y=1$

$$L(1,\hat{y}) = -(1 \log \hat{y} + (1-1)\log(1-\hat{y}))$$
$$= -\log \hat{y}$$

- since we always want smaller loss function value hence $\hat{y}$ should be very large (from 0 to 1) if it is the $-\log \hat{y}$ will be very large negative number or very small number.

when $y=0$

$$L(1,\hat{y}) = -(0 \log \hat{y} + (1-0)\log(1-\hat{y}))$$
$$= -\log(1-\hat{y}).$$

- Since we want smaller loss function value, hence $\hat{y}$ should be very small the automatically $(1-\hat{y})$ will be very large thus $-\log(1-\hat{y})$ will be large negative number or very small number.

- Cost function is nothing but mean average of loss function
- loss function (L) mainly applies for single training set as compared to cost function (J) which deals with a penalty for number of training set or complete batch.

loss function:

$$L(y, \hat{y}) = -(y \log \hat{y} + (1-y)\log(1-\hat{y})) \quad \text{— for single}$$

$$J(w,b) = \frac{1}{m}\sum_{i=1}^{m}(L(y^{(i)}, \hat{y}^{(i)})) =$$

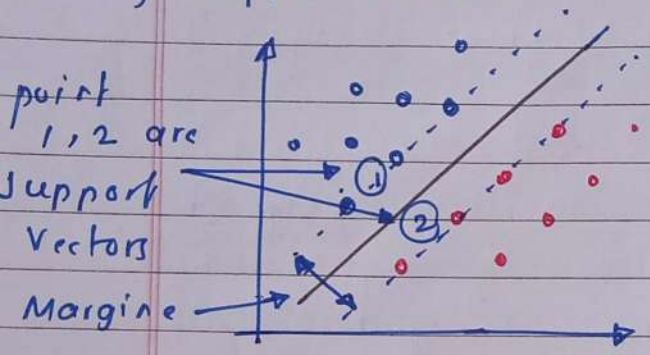
$$-\frac{1}{m}\sum_{i=1}^{m}\left(y^{(i)} \log \hat{y}^{(i)} + (1-y^{(i)})\log(1-\hat{y}^{(i)})\right)$$

{'m' denotes number of data points in the training set}.

Support Vector Machine (SVM)

Basic about SVM.

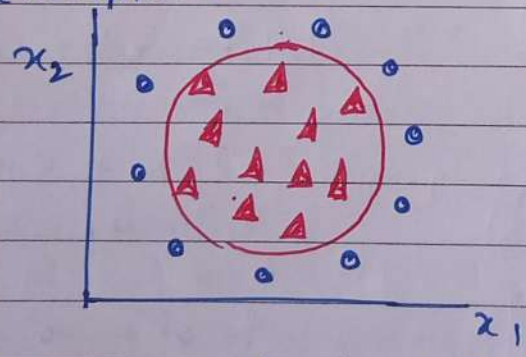
1) it is supervised ML model.
2) it can be used for both classification as well as regression but it is predominantly used for binary classification.
3) Hyperplane.
4) Support vectors



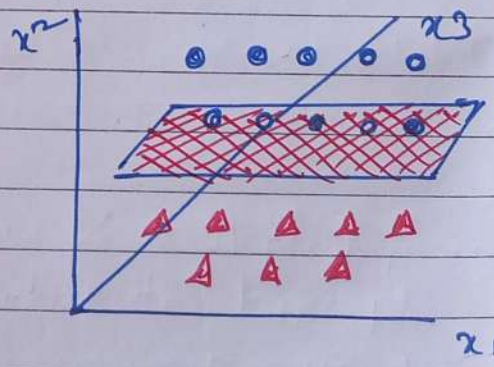
position of hyperplane depends upon support vectors.

- for 2D data it is easy to draw hyperplane but where data point can't seperated by line need to convert into 3D where we can seperate the datapoint by hyperplane

Example :-



{Here Not easy to seperate by line}



2D → 3D
and seperate by hyperplane

Hyperplan :- Hyperplane is line (in 2D) or plane that seperate the data point into two classes

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Support Vectors :- these are the datapoints which are nearest to hyperplane if these datapoints changes position of hyperplane changes.

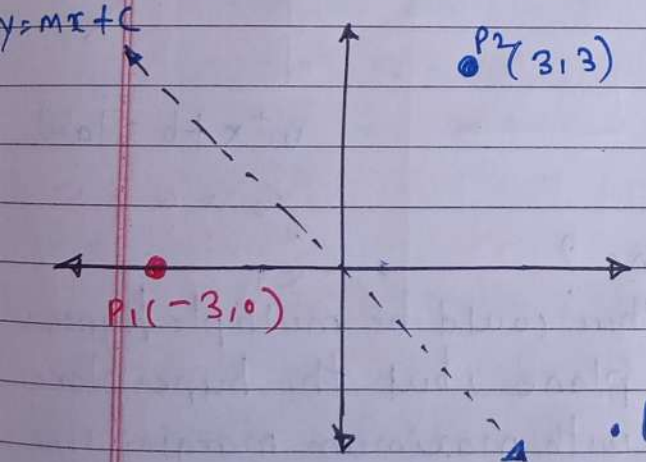
Advantages of SVM.

1) works fine with smaller dataset
2) works fine or efficiently where there is clear margin of seperation
3) work well with high dimensional data

Disadvantages

1) Not suitable for large dataset as training time would take very large.
2) Not suitable for noiser (outlier) dataset with overlapping classes.

Math Behind SVM.



let slope and intercept of hyperplane is,

$m = -1$

$c = 0$. {since passing through origine}

- let parameters of hyperplane sare in W which ir nothing but weight

$w \rightarrow (m, c) = (-1, 0)$

- let multiply x or P_1 by transpose of w

$$w^T x = \begin{bmatrix} -1 \\ 0 \end{bmatrix} \begin{bmatrix} -3 & 0 \end{bmatrix} = 3 \quad \text{(positive)}$$

[Note : why transpose ? → for matrix multiplication no of column of 1st Matrix must be equal ~~row~~ no. of rows of second matrix]

• positive value indicates all the points of hyperplane will be positive class.

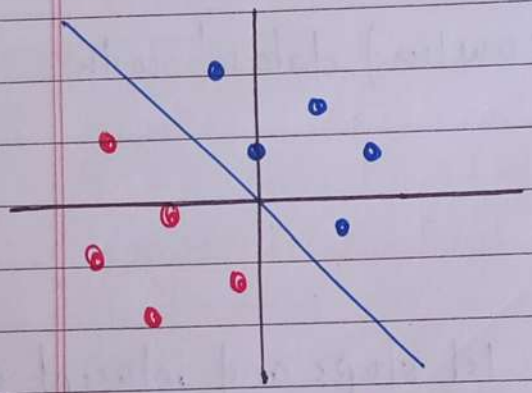
for $P_2(3,3)$

$$w^T x = \begin{bmatrix} -1 \\ 0 \end{bmatrix} [3,3]$$

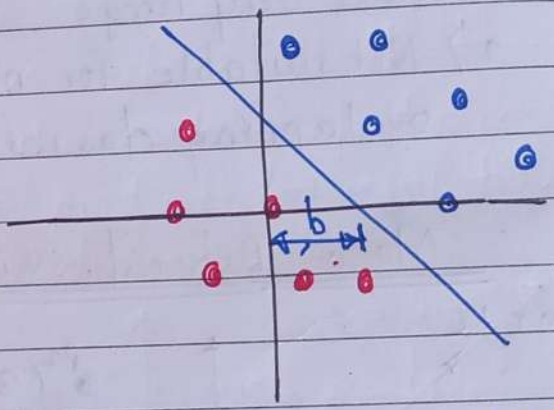
$$= -3 \quad (\text{Negative})$$

Here for all the points which lie on the right side of hyperplane will be belong to negative class.

But Not all the time hyperplane will pass through Origine.

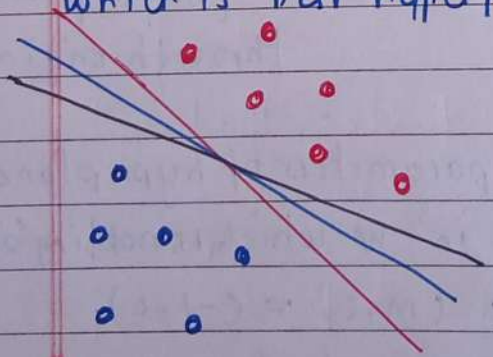


$w^T x = \text{label}$



$w^T x \neq b = \text{label}$.

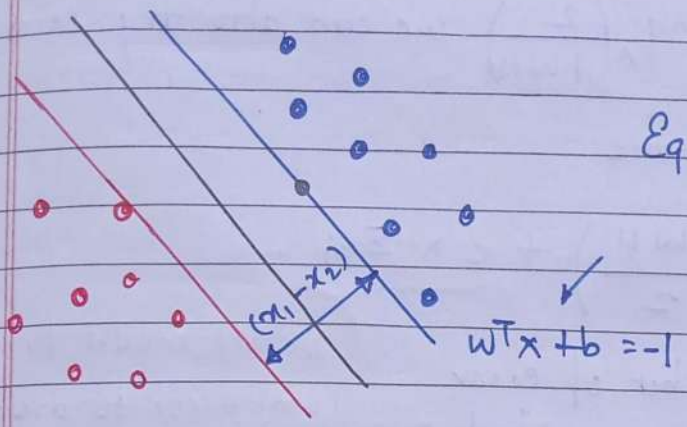
which is best hyperplane ?



there could be multiple hyperplane, but the hyperplane with maximum margine size will be the best hyperplane.

→ optimization for maximum margine

$w^T x + b = \text{label}$



Equation of point or blue support vector & its output value any negative value.

$w^T x + b = 1 \Rightarrow$ this is equation of point or red support vector and its output value could be any positive value

to get margine let substract one from another.

$$w^T x_1 + b = 1$$
$$(-)\ w^T x_2 + b = -1$$
$$w^T (x_1 - x_2) = 2$$

$$w^T (x_1 - x_2) = 2$$

divide both side by $\|w\|$

$$\frac{w^T (x_1 - x_2)}{\|w\|} = \frac{2}{\|w\|}$$

$$(x_1 - x_2) = \frac{2}{\|w\|}$$ ← this is nothing but magnitude of vector.

and

$$y_i = \begin{cases} -1 & w^T x_1 + b \leq -1 \quad \text{(label)} \\ 1 & w^T x_1 + b \geq 1 \end{cases}$$

so $\max \left(\frac{2}{\|w\|} \right)$ such that.

$$y_i = \begin{cases} -1 & w^T x_1 + b \leq -1 \\ 1 & w^T x_1 + b \geq 1 \end{cases}$$

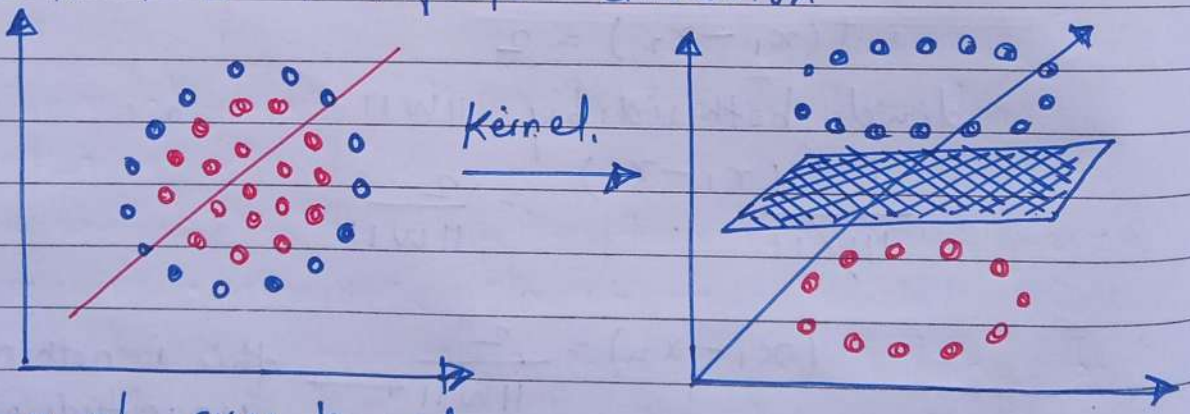
instead of using $\max_{\wedge}\left(\frac{2}{\|w\|}\right)$ we can also try Min which make better sense

$$\min\left(\frac{\|w\|}{2}\right) + \underbrace{c * \Sigma \varepsilon_i}$$

(we all model to train with some error to avoid overfitting (i.e it will be good and train and will bad for test data)

c : Number of error
ε_i : Error magnitude

Kernels' in SVM : Generally function of the kernel is to transform the training set of data so that non-linear decision surface can be transformed to a linear equation in higher number of dimension space it return the inner product between two points in standard feature dimension



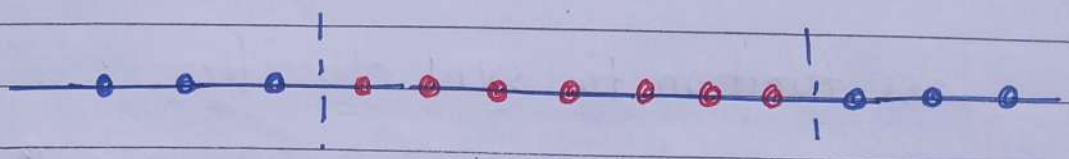
Type of SVM kernel.

1) Linear
2) polynomial
3) Radial Basis function. (rbf)
4) sigmoid.

Suppose feature (x)

x	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
x^2	36	25	16	9	4	1	0	1	4	9	16	25	36

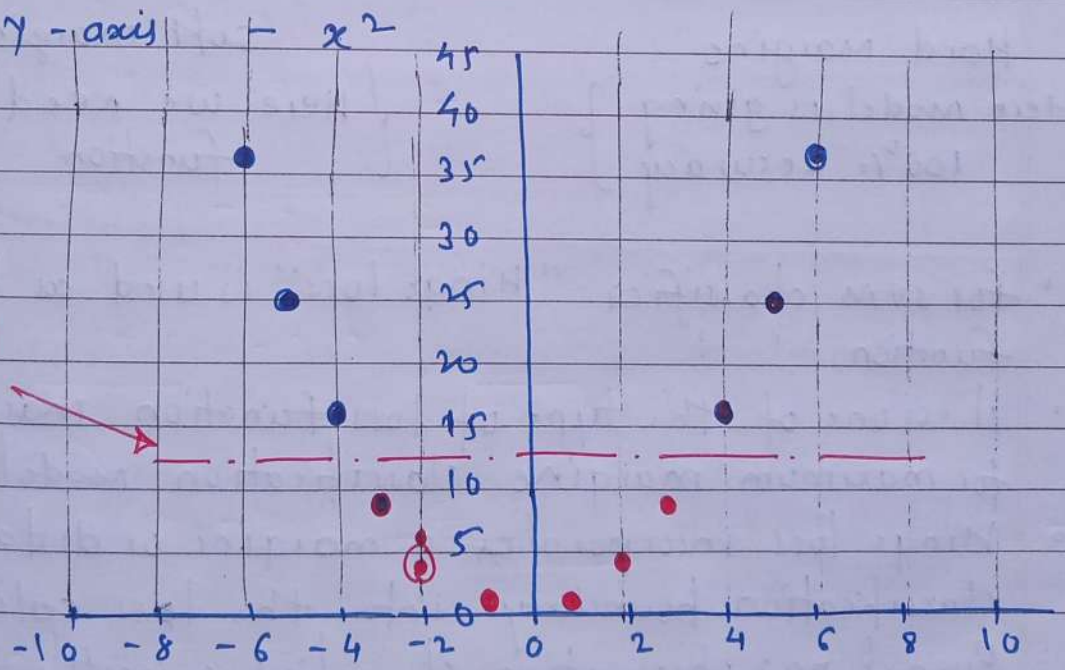
if you try to plot x on this 1D line.



- we can see None of the line could seperate the two class perfectly.
- that's why we add another feature which is function of x i.e x^2

x-axis - x

y-axis - x^2



Now this is seperable data.

1) Linear kernel :- $K(x_1, x_2) = x_1^T, x_2$
{best suitable for having too many features}

2) polynomial kernel.
$K(x_1, x_2) = (x_1 T x_2 + r)^d$.
d ↑ degree

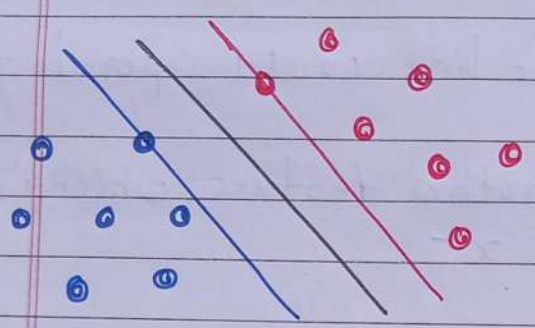
3.) radial basis function. (rbf kernel)

$$k(x_1, x_2) = \exp(-\gamma \cdot \|x_1 - x_2\|^2)$$

4. Sigmoid function

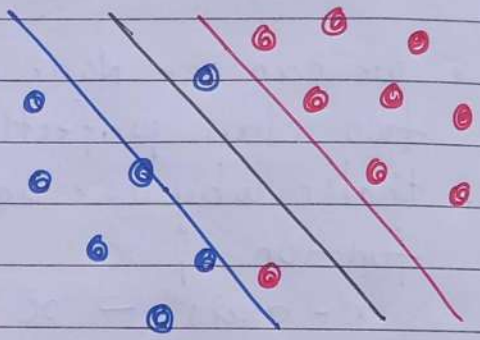
$$k(x_1, x_2) = \tanh(\gamma \cdot x_1^T x_2 + r)$$

Loss function for SVM classifier.



Hard Margine

{Here model is giving 100% accuracy}



soft margine

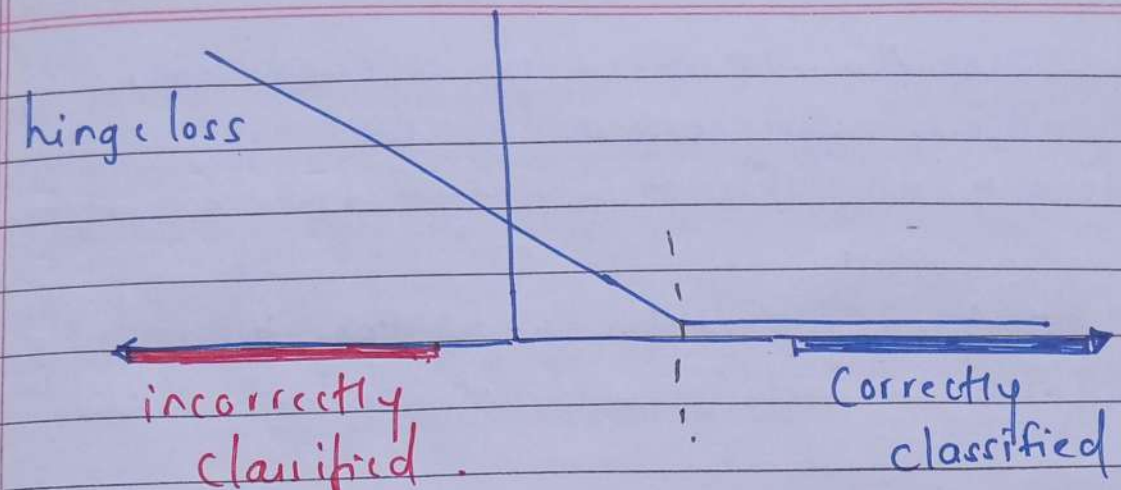
{Here we need loss function}

- for SVM classifier "Hinge loss" is used as loss function.
- it is one of the type of loss function mainly used for maximum margine classification model.
- Hinge loss incorporates a margine or distance from classification boundary into the loss calculation Even if new observation classified correctly they can incure penalty if the margine from decision Boundary is not large enough.

$$L = \max(0, 1 - y_i(w^T x + b))$$

0 - for correct classification

1 - for wrong classification.



let us for misclassification.

$y_i = 1$, $\hat{y}_i = -1$ $\quad$ $y_i = -1$ $\quad$ $\hat{y} = 1$

$L = (1 - 1(-1)$
$= 1 + 1$
$= 2$

$L = (1 - (-1)(1)$
$= 1 + 1$
$= 2$

{ both are high loss value }

Now let us for correct classification.

$y_i = 1$ $\quad$ $\hat{y}_i = 1$ $\quad$ $y_i = -1$ $\quad$ $\hat{y}_i = -1$

$(0 - (1)(1)$
$0 - 1$
-1

$(0 - (-1)(-1)$
$0 - 1$
-1

{ both are low loss value }

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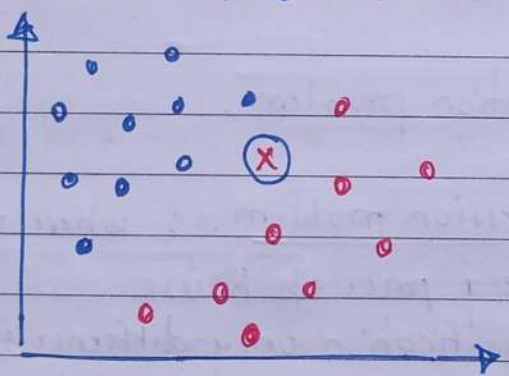
KNN - K-Nearest Neighbor.

- The abbrevation KNN stands for "K-Nearest Neighbor" it is supervised machine learning algorithm this algorithm can be used to solve both classification as well as regression problem.
- The number of nearest neighbor to a new unknown variable that has to be predicted or classified denoted by the symbol 'K'
- whenever new data will come if new data is close to 1 then prediction will be class 1 other wise 0 for binary classification same principle for multiclassification problem.
- In general K is odd number

Let understand with some example



Now we have to find new added (x)

Working of KNN Algorithm.

step 1: Lodding training as wellas test data.

step 2: Next we choose value of K (hyperparameter) the nearest datapoints. k can be any integer.

step 3: for each data point (new) test data do the following.

3.1) Calculate distance between test data and each row of training data with the help of distance calculating method. like Euclidian, Manhatten or Hamming distance. The most commonly method to calculate is Euclidian.

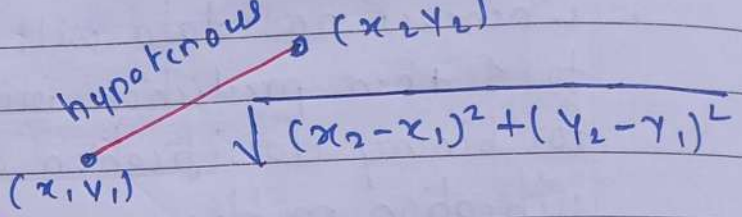
3.2) Now based on its distance value, sort them in ascending order.

3.3) Next it will choose the top k rows from sorted array.

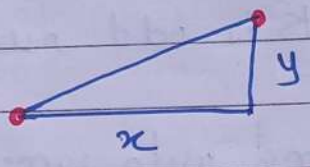
3.4) Now it will assign a class to a test point based on most frequent class of these rows.

Step 4 : End.

a) Euclidian distance :-



b) Manhattan distance



M. distance : $x+y$.

this is for classification problem.

Now let see for regression problem. : where output is continuous data. e.g price of house.

). it is similar to classification only difference in last step where we were considering most frequent class here from k number of output (nearest 'k') we calculate their mean, that's it

Limitation : Not applicable to huge dataset since calculating distance would consume lot of time

- Sensitive to outliers
- Sensitive to missing values

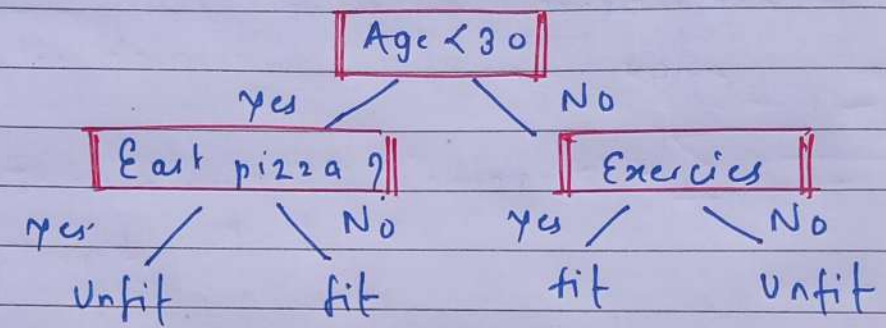
Desion Tree.

Ahout decision Tree.

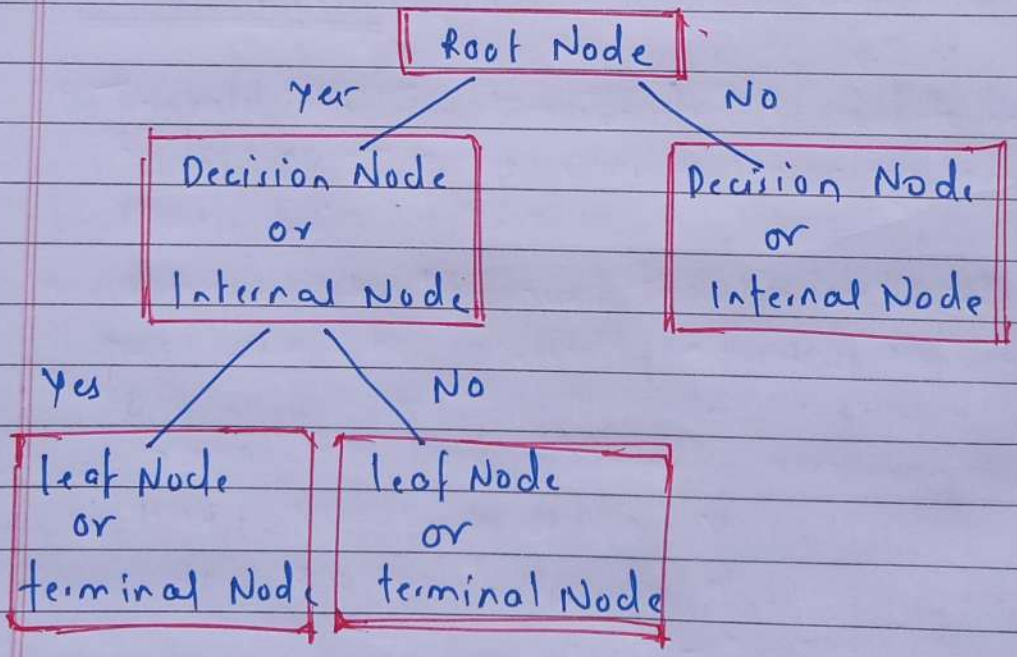
1) it is supervised ML Model
2) Used both classification & Regression.
3) Build Decision Nodes at each step.
4) Basis of Tree based model.

let understand with Example.

is person fit or Not?



Structure & terminology of DT :-



Advantages :-

1) . Can be used for both classification & Regression
2) . Easy to interprete
3) No need for Normalization or scaling
4) Not sensetive to outliers.